Storypoint Problem Exploration - springxd

September 5, 2024

1 Storypoint Prediction: Problem Exploration

1.1 Problem Statement

In modern agile development settings, software is developed through repeated cycles (iterative) and in smaller parts at a time (incremental), allowing for adaptation to changing requirements at any point during a project's life. A project has a number of iterations (e.g. sprints in Scrum). Each iteration requires the completion of a number of user stories, which are a common way for agile teams to express user requirements.

There is thus a need to focus on estimating the effort of completing a single user story at a time rather than the entire project. In fact, it has now become a common practice for agile teams to go through each user story and estimate its "size". Story points are commonly used as a unit of measure for specifying the overall size of a user story.

1.2 Problem Formulation

Input: A string of length N that contains a story's name and description $C = \{c_1, c_2, c_3, ..., c_n\}$. For each story, a set of text embeddings that contains features $E = \{e_1, e_2, e_3, ..., e_m\}$ extracted from C has been provided.

Output: A natural number P associated with the story point of that user story

1.3 Dataset Information

Text Embeddings: Text embeddings are a way to convert words or phrases from text into a list of numbers, where each number captures a part of the text's meaning. The dataset has been preprocessed and converted into two kinds of text embeddings. You can choose to work with either of them or both: - Doc2Vec: Input strings are transformed into fixed-length vectors of size 128. These vectors capture the semantic meaning of words and their relationships within a document. - Look-upTable: Input strings are transformed into fixed-length vectors of size 2264. These vectors are obtained via transforming each word in the input strings into an identifier number, then padded to the length of the longest sample.

Dataset Structure & Format: Storypoint Estimation Dataset is stored in 3 folders labeled *raw data*, *look-up*, and *doc2vec*. Within each folder are 3 CSV files for training, testing, validation. Each csv file has the following columns: - `issuekey` : The unique identifier for a story. - `storypoint`: The correct number of storypoint. - An embedding column (`embedding` or `doc2vec`) contains text embedding vectors. The raw data csv will not have this and instead contain two columns with story `name` and `description`.

1.4 Exploration

1.4.1 Raw data exploration

[ ]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns

from sklearn.feature_extraction.text import CountVectorizer
```

Output exploration

[ ]:
```
# Import raw data from the CSV file

project_name = 'springxd'

all_data = pd.concat([pd.read_csv('data/' + project_name + '/' + project_name +␣
 ↪'_train.csv'),
                      pd.read_csv('data/' + project_name + '/' + project_name +␣
 ↪'_valid.csv'),
                      pd.read_csv('data/' + project_name + '/' + project_name +␣
 ↪'_test.csv')])

print('Check the shape of the dataset', all_data.shape)
```

```
Check the shape of the dataset (3056, 4)
```

[ ]:
```
all_data.drop(['issuekey'], axis=1, inplace=True)
all_data.head()
```

[ ]:

	title	description	storypoint
0	hdfs itemwriter	base integration core hdfs writer functionalit…	1
1	hdfs core writing helper classes	simple file writer existed spring hadoop samples	1
2	tuple data structure	tuple data structure backward compatible funct…	1
3	syslog ingestion	syslogxml config file added module registered …	1
4	reactor based http ingestion	support boostrapping http server reactor proje…	5

First, let take a look at the distribution of the story point:

Interpretation of Skewness Values:

- **Skewness $>$ 0**: Right-skewed distribution.
- **Skewness $<$ 0**: Left-skewed distribution.

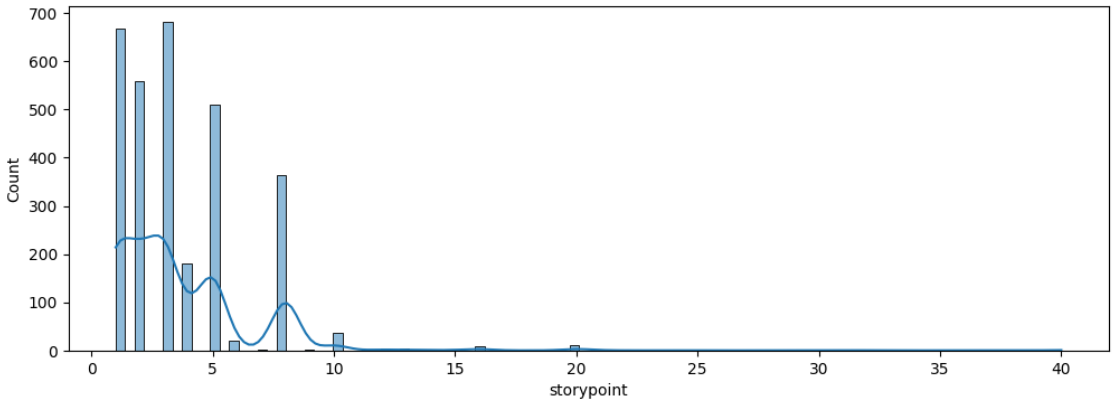
- **Skewness = 0**: Symmetrical distribution (like a normal distribution).

Interpretaion of kurtosis: - **Leptokurtic (Kurtosis > 3)**: The distribution has heavier tails and a sharper peak than the normal distribution. Data points are more likely to produce extreme values. The distribution has a higher peak and fatter tails. - **Platykurtic (Kurtosis < 3)**: The distribution has lighter tails and a flatter peak than the normal distribution. Data are fewer extreme values compared to a normal distribution. - **Mesokurtic (Kurtosis 3)**: The distribution has a similar kurtosis to the normal distribution, indicating a moderate level of outliers.

[ ]:
```
# Draw a histogram of the story points
plt.figure(figsize=(12, 4))
plt.xticks(np.arange(0, max(all_data['storypoint']) + 1, 5))
sns.histplot(all_data['storypoint'], bins=100, kde=True)

print('Skewness:', all_data['storypoint'].skew())
print('Kurtosis:', all_data['storypoint'].kurt())
```

```
Skewness: 3.1604713763235495
Kurtosis: 24.244205825538867
```



[ ]:
```
tmp = pd.concat([all_data['storypoint'].value_counts(),
                 all_data['storypoint'].value_counts() / all_data.shape[0] *␣
 ↪100],
                axis=1, keys=['Counts', 'Percentage (%)'])
tmp.head(20)
```

[ ]:

storypoint	Counts	Percentage (%)
3	681	22.284031
1	667	21.825916
2	558	18.259162
5	511	16.721204
8	365	11.943717
4	180	5.890052

10	37	1.210733
6	20	0.654450
20	10	0.327225
16	9	0.294503
12	5	0.163613
13	3	0.098168
40	2	0.065445
15	2	0.065445
21	1	0.032723
14	1	0.032723
9	1	0.032723
7	1	0.032723
24	1	0.032723
32	1	0.032723

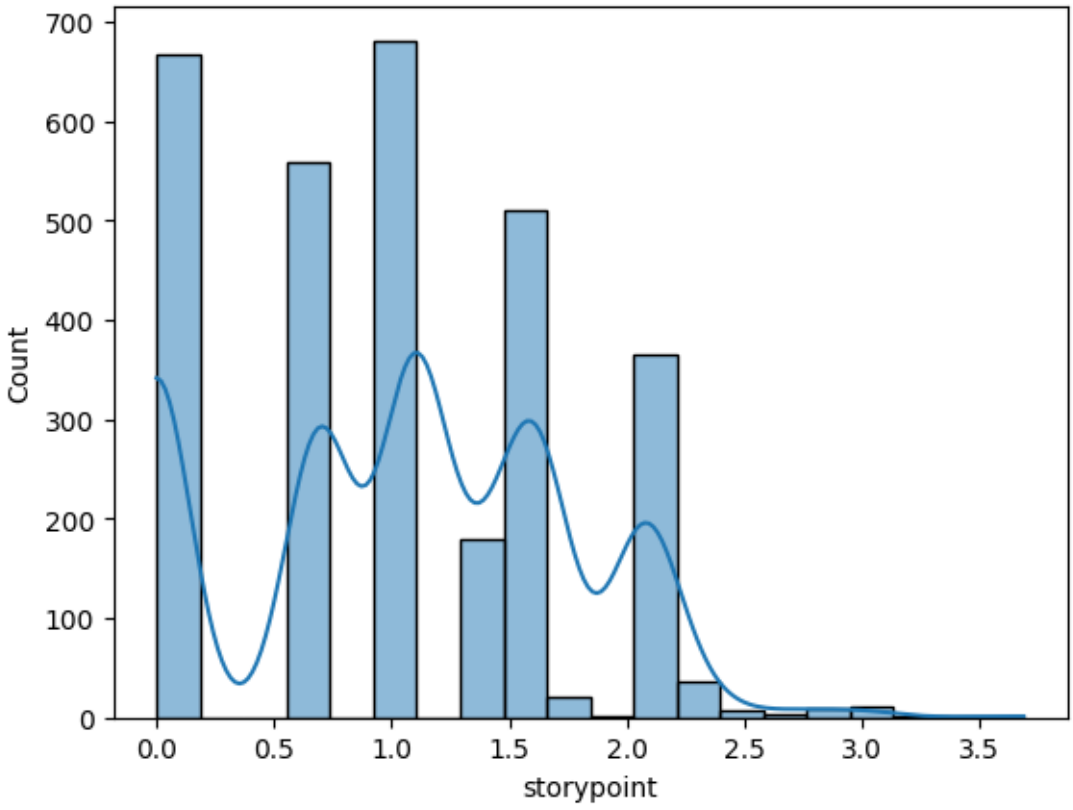
At the first sight, this data is bad. Then take a look at the statistic values, this data is even worse. Its distribution of the label is **right-skewed** and **leptokurtis**. This means if we use this to train model, the right side of the data can be the outliers and make the models become unsuable.

I will try 2 solutions: - Use log-scale on the label - Remove all the examples with label greater than a threshold (20, 30 or 40)

The first solution: logarithm magic

[ ]:
```
sns.histplot(np.log(all_data['storypoint']), bins=20, kde=True)
```

[ ]:
```
<Axes: xlabel='storypoint', ylabel='Count'>
```



[ ]:
```
print('Skewness:', np.log(all_data['storypoint']).skew())
print('Kurtosis:', np.log(all_data['storypoint']).kurt())
```

```
Skewness: 0.030072206325719636
Kurtosis: -0.7130091211568881
```

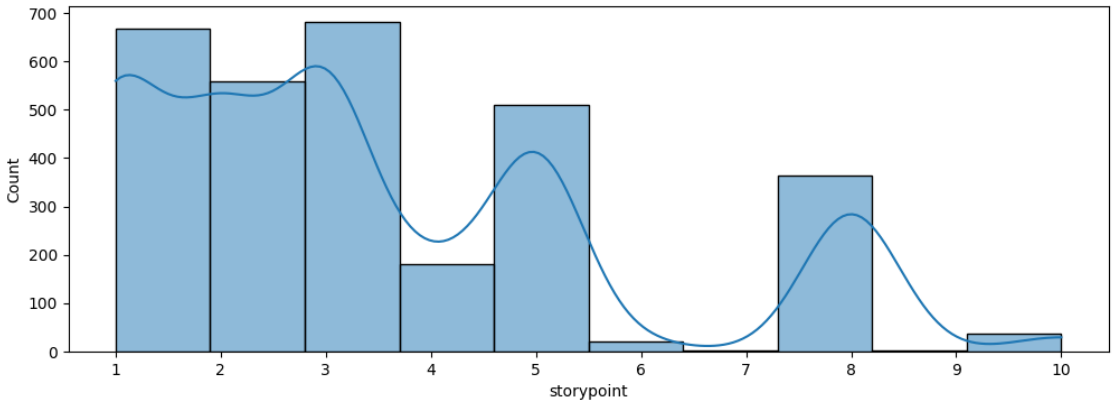
Kurtosis now is negative, but still near 3 than before. Skewness is near 0 which is very good

The second solution: Dismantle and Cleave

[ ]:
```
threshold = 10 # This threshold means that we will take all the examples with␣
 ↪story points less than or equal to 10

new_data = all_data[all_data['storypoint'] <= threshold]
plt.figure(figsize=(12, 4))
plt.xticks(np.arange(0, max(new_data['storypoint']) + 1, 1))
sns.histplot(new_data['storypoint'], bins=threshold, kde=True)
print('Fitered percentage: ', round(1 - new_data.shape[0] / all_data.shape[0],␣
 ↪2) * 100, '%')
```

```
Fitered percentage:  1.0 %
```



Input exploration The input of this problem is 2 texts: title and description. First we will find some statistics:

[ ]:
```
title_lengths = all_data['title'].apply(lambda x: len(x.split(' ')))
print('Title analysis:')
print('   - Mean length:', round(title_lengths.mean()))
print('   - Min length:', title_lengths.min())
print('   - Max length:', title_lengths.max())

description_lengths = all_data['description'].apply(lambda x: len(x.split(' '))␣
 ↪if type(x) != float else 0)
print('Description analysis:')
print('   - Mean length:', round(description_lengths.mean()))
print('   - Min length:', description_lengths.min())
print('   - Max length:', description_lengths.max())
```

```
Title analysis:
   - Mean length: 5
   - Min length: 1
   - Max length: 17
Description analysis:
   - Mean length: 31
   - Min length: 0
   - Max length: 629
```

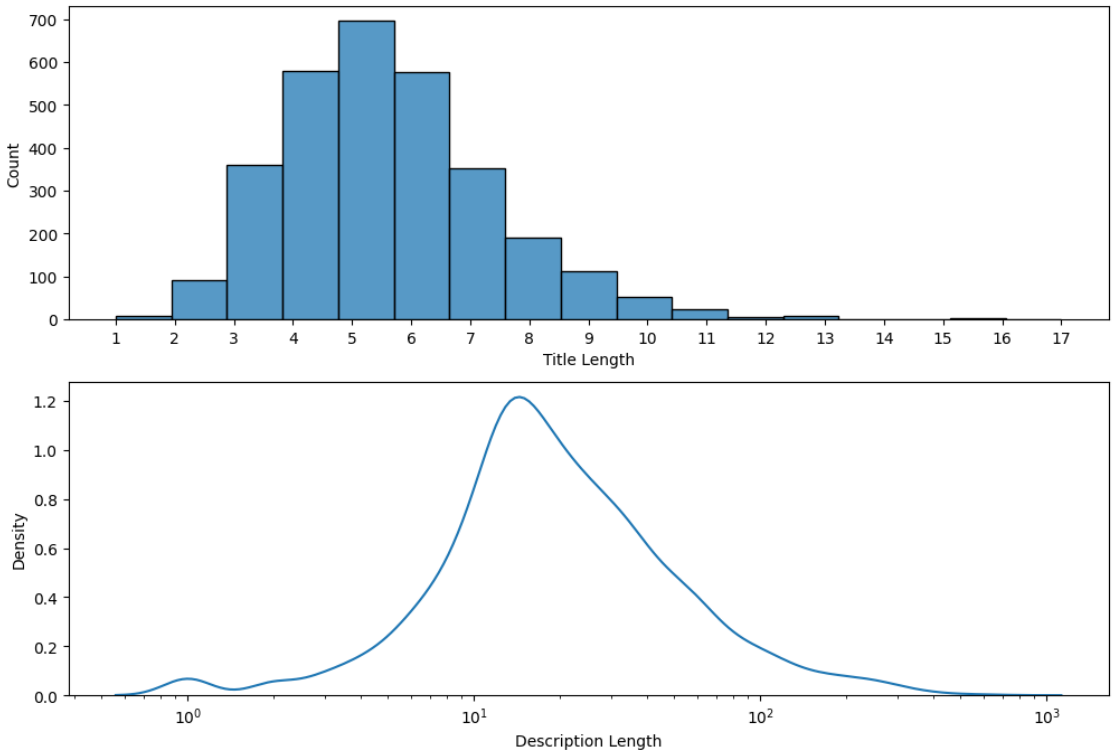
Plot the histogram of the title length and KDE of the description length (exclude 0):

[ ]:
```
plt.figure(figsize=(12, 8))

plt.subplot(2, 1, 1)
plt.xticks(np.arange(0, max(title_lengths) + 1, 1))
plt.xlabel('Title Length')
sns.histplot(title_lengths, bins=max(title_lengths))
```

```
plt.subplot(2, 1, 2)
plt.xlabel('Description Length')
plt.xscale('log')
sns.kdeplot(description_lengths[description_lengths > 0])
```

[ ]: <Axes: xlabel='Description Length', ylabel='Density'>



I think we should check the correlation between title length and description length:

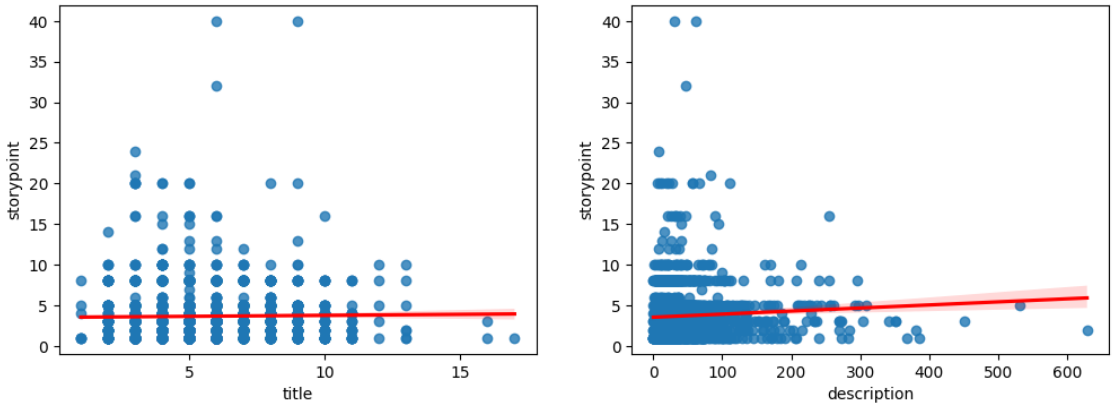
[ ]:
```
plt.figure(figsize=(12, 4))

plt.subplot(1, 2, 1)
plt.xticks(np.arange(0, max(all_data['title'].apply(lambda x: len(x.split('␣
↪')))) + 1, 5))
sns.regplot(x=all_data['title'].apply(lambda x : len(x.split(' '))),
            y=all_data['storypoint'],
            line_kws={'color': 'red'})

plt.subplot(1, 2, 2)
sns.regplot(x=all_data['description'].apply(lambda x : len(x.split(' ')) if␣
↪type(x) != float else 0),
            y=all_data['storypoint'],
```

```
            line_kws={'color': 'red'})
```

[ ]: <Axes: xlabel='description', ylabel='storypoint'>



This is surprising (after about 10 datasets I worked with in this project). We can see a slight slope on the left and a obivious slope on the right. The best thing to be observed in these plots is that the deviation is really small. I hope in the training part, the features of description length and title play a good role in the model.

Let dive deeper in the input:

Title analysis:

[ ]:
```
count_vectorizer = CountVectorizer()
count_vectorizer.fit(all_data['title'])

dictionary = pd.DataFrame(list(count_vectorizer.vocabulary_.items()),␣
 ↪columns=['word', 'frequency'])
dictionary.sort_values(by='frequency', ascending=False, inplace=True)
print(dictionary.shape)
dictionary.head(10)
```

```
(3090, 2)
```

[ ]:

	word	frequency
2472	zookeeperstreamrepositoryfindallinrange	3089
2467	zookeeperstreamrepository	3088
1977	zookeepercontainerrepository	3087
2556	zookeeperbased	3086
1575	zookeeper	3085
2163	zone	3084
2308	zmq	3083
2148	zks	3082
1745	zkcurator	3081

126	zip	3080

Description analysis:

```
[ ]: count_vectorizer = CountVectorizer()
count_vectorizer.fit(all_data[all_data['description'].isnull() ==␣
 ↪False]['description'])

dictionary = pd.DataFrame(list(count_vectorizer.vocabulary_.items()),␣
 ↪columns=['word', 'frequency'])
dictionary.sort_values(by='frequency', ascending=False, inplace=True)
print(dictionary.shape)
dictionary.head(20)
```

```
(12331, 2)
```

[ ]:

	word	frequency
12078	zzz	12330
82	zset	12329
7204	zookeeperzookeeperjobrepository	12328
6242	zookeeperzookeeperconnection	12327
5998	zookeeperzookeeper	12326
10162	zookeeperutilsmaptobytesstatustomap	12325
10158	zookeeperutilsgetstacktracee	12324
9440	zookeeperstreamrepositoryfindallinrange	12323
9422	zookeeperstreamrepository	12322
8141	zookeepermoduledefinitionrepository	12321
12106	zookeeperlog	12320
12124	zookeeperjar	12319
5833	zookeeperexceptionhandler	12318
7093	zookeepercontainerrepository	12317
7135	zookeeperconnectionlistener	12316
5533	zookeeperconnection	12315
6224	zookeeperclientcnxn	12314
5320	zookeeper	12313
10969	zoocfg	12312
7273	zone	12311

Yet I don't find any thing special about the words in input except so many things are bad.

1.4.2 Solving strategies

My first intuitation in this problem is that the hard part is not on the algorithm we use, it is on the **embedding** part. Therefore, in case the given embedded datasets work not properly, I will use a better embedding method which is **Bidirectional Encoder Representations from Transformers (BERT)**. Also, I will try an old way to embedding the text too: **Bag of words**.

In conclusion, I will have 4 ways to embed the text: - doc2vec (already available) - Look up (already available) - Bag Of Words - BERT

About algorithm, I will try all the regression algorithm that may give a good result:

- Ridge Regressor
- Support Vector Regressor
- Random Forest Regressor
- Gradient Boosting
- XGBoost
- Lightgbm
- Blended

Maybe, we can change the problem to the classification problem with 100 labels (desparation confirmed). In the classification problem, I will use: - Support Vector Classifier - Softmax Regression (Multinomial Logistic Regression) - Random Forest - Adaboost - XGBoost

Thanks to the libaries, the implementation of all the algorithm shrinks to its minimum form.

At last, there is still a situation that all of mentioned model don't give a good result. This gamble is thrilling (hopeless).

"But would you lose?"

Nah, I'd win.